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# Energy consumption and economic growth in South Africa reexamined: A nonparametric testing apporach

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ABSTRACT

This paper is an effort to investigate claims concerning Granger causality relationship from energy consumption to economic growth in South Africa. We adopt a nonparametric bootstrap method to reassess evidence supporting Granger causality and unravel findings of long-run unidirectional causality running from energy consumption to economic growth. This implies that energy conservation policies will negatively impact economic growth in South Africa. In addition, the results of this study have implications on CO2 emissions in South Africa given that coal accounts for about 72% of energy. This suggests that energy use would have a long run effect of raising the country's $CO_2$ emission levels. Hence, there might be a need to develop a more balanced energy structure which will include higher share of renewable energy. A further Monte Carlo experiment performed reveals that asymptotic Granger causality test suffers size distortion problem for South African data. These findings provide support for use of a bootstrap methodology and also imply that the results presented in this study are likely to be more reliable.



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## 1. Introduction

One of the most debated topics abroad over the past decades has been the issue of energy consumption and economic growth. This interest has not only been fueled by the increasing economic activities across countries which have triggered a growing demand for energy across the world, but the notion that energy prices directly affect spending decisions of households, firms, and the overall performance of the economy as well. The direction of causality is highly relevant for policy makers. For instance, if causality runs from energy consumption to economic growth, energy conservation policies that have the aim of reducing energy consumption may have a negative impact on an economy's growth. The literature proposes four different hypotheses regarding the possible outcomes of causality and there have been studies for OPEC countries, G7 countries, Asian countries, African countries, etc. (see [1]).

South Africa is an energy-intensive economy. According to the US Energy Information Administration, coal alone accounted for about 72% of total primary energy consumption in 2012. Hence, a discussion on the subject of energy consumption and the South African economy would be unbalanced without mentioning the implications on $CO_2$ emissions. South Africa alone accounts for about 42% of Africa's emissions [2]. According to IEA [3], South Africa is ranked as the world's most carbon-intensive non-oil-producing developing country. Thus, a study of this nature would also help to provide policy-makers with sound and informed energy supply and demand choices necessary to address $CO_2$ emissions in Africa.

A number of authors have attempted to investigate the nature of causal links between energy consumption and economic growth in African countries. Notwithstanding, majority of the studies for South Africa are multi-country (see [1,4,5]) for a discussion of energy consumption – economic growth nexus studies for Afrian countries. A notable exception is Odhiambo [6] who employed a dynamic Granger causality test based on asymptotic theory to investigate the nature of causal links between electricity consumption and economic growth in South Africa using annual data covering the period 1971–2006. Our motivation for the present study comes as follows: first, South Africa is the largest economy on the continent of Africa and influences policy decisions of many other African countries. Hence, the need for more country-specific studies as basis for concluding the direction of causality becomes imperitive. Second, as a proxy for electricity consumption, most studies for South Africa including Odhiambo [6] used the residential electricity consumption/capita. Eventhough residential electricity consumption accounts for 17% of electricity demand, this might not reflect the true welfare or income level for a country like South Africa given that the country has one of the lowest electricity prices in the world. More besides, the free basic electricity subsidy in South Africa which entitles all households to 50 kWh of electricity every month is likely to influence residential demand and consumption patterns. As an alternative, this study uses the industrial electricity consumption. Indeed, the industrial sector is the largest user of energy and the largest user of electricity and accounts for over 66.9% of South African total electricity consumption [7]. Finally, the type of data used for time series studies on South Africa makes the test results a bit skeptical. The total number of observations in the asymptotic Granger causality test for all known studies usually do not exceed 36. Even though one may argue that 36 observations satisfy the minimum requirement for establishing statistical power, conducting the asymptotic test with only 36 observations may lessen the creditability of the test result because the sample size is small.

The small-sample problem is very likely to occur in this case. Furthermore, the method requires modeling assumptions (such as linearity of the regression structure, etc.) and hence, the application of asymptotic theory may lead to spurious results if suitable modeling assumptions do not hold (see [8,9]). Moreover, the tests based on prediction errors will be sensitive only to causality in the mean, while higher order structure such as heteroskedasticity, will be ignored (see [10,11]). In addition, it is now known that standard asymptotic distribution theory may often cause significant over-rejection of the non-Granger causality null hypothesis (e.g., [1]). Hence, this suggests that in order to obtain more robust estimates of causality would require implementation of a more general testing method which is sensitive also to nonlinear causal relationships and overcomes the above difficulties. Surprisingly, even recent studies for South Africa fail to acknowledge these shortcomings (e.g., [12,13]).

In order to reassess the existing evidence of the Granger causality relationship between energy consumption and economic growth in South Africa, this study employs an alternative testing method which departs from standard traditional approaches. Efron [14] pioneer a bootstrap testing technique which is less sensitive to possible model misspecification such as neglected nonlinearity, time series properties and size distortion. These features make application of the bootstrap technique particularly attractive for a country like South Africa not least because of the need to adopt a different testing technique, but also because of evidence of heteroskedasticity in the data (as revealed by White's hetereskedasticity test) as well as the relatively small sample size (40 observations in our case). Unlike traditional approaches, the method is used for estimating the distribution of a test statistic by resampling the data non-parametrically. Since the estimated distribution depends only on the available dataset, it may be reasonable to expect that the bootstrap approach does not require such strong assumptions as traditional methods. Even though this approach has been shown to reduce size distortions (as we also show in this paper) and is believed to provide more precise test inferences than the asymptotic method in many applications especially when the available sample size is small [1,7,8,15–18] this paper will be one of the first applications of the bootstrap technique to any African country; second only to Wesseh and Zoumara [1].

As in Ko [9], to explore the potential benefit of using a bootstrap method in estimating the causal links between energy consumption and economic growth in South Africa, we examine its test size and power properties[1] relative to the asymptotic method. To this end, we conduct a Monte Carlo study to investigate whether the asymptotic test had larger size distortion than the bootstrap test in this application. Results from the experiment showed that the asymptotic test had larger size distortion than the bootstrap test thus implying that the asymptotic Granger causality test suffers size distortion problem for South African data. Given that previous evidence of causal links between energy consumption/electricity consumption and economic growth in South Africa relies on asymptotic results, the need for more evidence from alternative testing methods becomes important.

The rest of this paper is organized as follows. Section 2 presents an overview of energy/electricity consumption in South Africa. Section 3 describes the Granger causality approaches. Section 4 provides a summary statistics of the data and the empirical results. Section 5 concludes the paper providing some policy implications.

[1] For details surrounding this kind test, interested readers are referred to Ko [9], Horowitz [19], Dolado and Lütkepohl [20], Davidson and MacKinnon [21], Mantalos [17], Diks and DeGoede [10], Hacker and Hatemi [8], Lach [18], etc. It should be mentioned that for the sake of conserving space, we only present Monte Carlo results for the primary energy consumption analysis. Results for total electricity consumption are available upon request from the authors.

## 2. Overview of energy/electricity consumption and economic growth in South Africa

The energy sector of South Africa is important as the country relies heavily on its largescale, energy-intensive industry which in this paper includes mining, manufacturing, construction and all processing except the processing of energy from one form to another. In other words, the country has a large and dynamic energy economy, with high energy intensity. According to the Energy Outlook for South Africa, between the years 2000 and 2010, the South African Industrial Sector accounted for slightly over 43.4% of South Africa's total final energy consumption (1325 PJ out of 3055 PJ) and 66.9% of electricity (410 PJ out of 612 PJ). This makes the Industrial Sector the largest user of energy and the largest user of electricity. Since 1971–2010, manufacturing alone has contributed between 21.8% and 25% of GDP. In South Africa, there are only meager deposits of conventional oil and natural gas. As such, the country uses its large coal deposits for bulk of its energy needs, thus making the industrial sector a major coal user. In addition, South Africa has a well developed synthetic fuels industry which produces gasoline and diesel fuels from coal and natural gas. As indicated by IEA data, primary energy and electricity increased by an average of 3.7% and 3.9% respectively per annum during the previous decade. A breakdown of primary energy utilization in South Africa follows: Coal (71%); crude oil (15%); renewable (10%); nuclear power (1.5%); natural gas (1.5%) hydro-electric power ( $<1$%). According to IEA [3], in 2008, South Africa total consumption of energy amounted to an equivalent of 5.3 quadrillion Btu. Coal resources alone were estimated at about 33 billion short, accounting for 95% of African coal reserves and close to 4% of world reserves. As a matter of fact, coal is a significant feedstock for South Africa's synthetic fuel industry. The production and consumption of coal has maintained relatively stable levels over the past decade. In 2010, an estimated 276 million short-tons and 201 million short tons (MMst) were produced and consumed respectively. The remaining 75 MMst were exported, mostly to China, India, and Europe.

The electricity system has grown rapidly during the last few decades with over 90% of the country's electricity coming from coal power stations. As the highest in Sub-Saharan Africa, South Africa has reached a 75% rate of electrification nationwide. However, only 55% of the rural population has access to electricity, compared to 88% in urban areas. According to IEA [3], the above sttistics indicate that about 12.5 million South African had no access to electricity. In recent years, the demand for electricity continues to rise. Although improvements have taken place, the increasing demand in most cases outstripped the available supply thus leading to a situation of rolling blackouts. In the 2010 electricity strategy, there are provisions for independent power producers to hep improve the distribution structure and fast-tracking of electricity projects. Investment in new power projects with targeted capacity of over 40,000 MW is expected to be achieved by 2030. Coal, renewables and nuclear generating capacity would form a lion-share of such investment. Three coal fire power stations have already been re-commissioned with plans underway for another 4700 MW coal-fired plant as well as a 3500 MW nuclear power station. Due to financial reasons and possible security concerns following Fukushima, the nuclear project has been delayed. South African electricity rates have been increasing gradually for all sectors not least as a demand-side measure, but also to be able to meet generation targets. These have created serious concerns among energy-intensive industries as well as poorer households. Eskom generates approximately 95% of South Africa's electricity, which comes mainly from coal fired plants. According to statistics provided by the company's website, in 2008 Eskom had a total generation capacity of 50.2 gigawatts (GW), 85% of which is from coal fired plants (42.5 GW including return-to-service and new build plants). Close to 7% of the country's generating capacity is from the Koeberg Nuclear Power Station. South Africa also exports electricity to neighboring countries through the Southern African Power Pool (SAPP).

## 3. Cointegration and Granger causality approaches

In this section, we present the cointegration approaches employed and justify our choice of the methods. In addition, we describe some traditional Granger causality approaches as well the the bootstrap technique.

### 3.1. Cointegration

Since all variables in this study are I(1) as shown in the stationarity analysis in Table 2, we test for co-integration and subsequently estimate the long-run elasticities. We use the cointegration test suggested by Pesaran et al. [22]. The main reasons for adopting this approach are as follows: First, the method is not sensitive to the size of the sample, therefore making its small sample properties more superior to the multivariate cointegration approach. Thus, it does not suffer in finite samples from possibly invalid common factor restrictions. This should be of importance since our dataset consists of only 40 observations. Second, the ARDL approach is known to provide unbiased long-run estimates even when some of the variables are endogenous. Narayan [23] and Odhianbo [24] as quoted in Wesseh and Niu [25] demonstrates that even when some of the independent variables are endogenous, the bounds testing approach generally provides unbiased long-run estimates and valid *t*-statistics. One disadvantage of this method however is the fact that the bounds test does not provide the dimession of the cointegration space. To avoid random assumption of the number of cointegrating vectors for our VEC model, we also employ the Johansen–Juselius cointegration tests which demonstrated evidence of a unique cointegrating vector between primary energy/total electricity consumption, employment and economic growth for all sample periods (see Table 1 for a description of variables and symbols). We therefore assumed a 1 cointegrating vector[2] for all cases. Since both the bounds test and Johansen–Juselius techniques have been well popularized for testing the long-run relationships among variables, we will not explain them here in order to conserve space. Interested readers are referred to the relevant literature for detailed discussion and advantages of these methods.

### 3.2. Granger causality approaches

#### 3.2.1. Traditional Granger causality approaches

In this literature, Granger's [26] test for causality has been widely used. In fact, since the development of this concept, a number of studies examining properties of different testing methods have been published. One of the first approaches was the standard Wald test based on asymptotic distribution theory. As noted by Lach [18], the biggest advantage of this method was its simplicity and clarity. Notwithstanding, the standard asymptotic approach turned out to be an improper tool for testing the causal effects in cases where the variables were integrated of order one (I (1)) or cointegrated. In other words, the standard Granger causality test may not identify such

[2] The vector which we denote as$ECM_t$involved$Y_t$and$ENG_{1t}$for the analysis of primary energy consumption and economic growth and $Y_t$and$ENG_{2t}$ for the analysis of total electricity consumption and economic growth. The results of the Johansen–Juselius test are not presented in this paper but available upon request from the authors.

**Table 1**
Variable description and symbol.

| Description of variable | Symbol |
|---|---|
| Economic growth in South Africa proxy by real GDP | $Y_t$ |
| Primary energy consumption in South Africa | $ENG_{1t}$ |
| Total electricity consumption in South Africa | $ENG_{2t}$ |
| Employment in South Africa based on total public and private sectors excludingthe agricultural sector | $EMP_t$ |

**Table 2**
Stationarity tests.

| Variable | ADF | | | PP[a] | | |
|---|---|---|---|---|---|---|
| | Full sample | Pre-transformation period | Post-transformation period | Full sample | Pre-transformation period | Post-transformation |
| $Y_t$ | 0.99 | 0.40 | 0.27 | 0.99 | 0.83 | 0.75 |
| $ENG_{1t}$ | 0.62 | 0.93 | 0.63 | 0.61 | 0.94 | 0.71 |
| $ENG_{2t}$ | 0.60 | 0.98 | 0.22 | 0.69 | 0.98 | 0.74 |
| $EMP_t$ | 0.32 | 1.00 | 0.28 | 0.79 | 0.97 | 0.60 |

*Note*: All values reported indicate p-values of nonstationarity of the series. Further calculations show that all nonstationary series are first difference stationary or I(1).

[a] The bandwidth parameter was established according to Newey and West [34].

**Table 3**
Cointegration analysis based on the bounds tests.

| Full sample | | | |
|---|---|---|---|
| Variables (ARDL lag specification) | *F*-stastics | Critical value bounds | |
| | | {I(0) | I(1)} |
| $Y_t, ENG_{1t}, EMP_t$ (1,0,1) | 5.782[a] | {4.19 | 5.06} |
| $Y_t, ENG_{2t}, EMP_t$ (1,0,1) | 5.195[b] | {3.38 | 4.02} |
| Pre-transformation period | | | |
| $Y_t, ENG_{1t}, EMP_t$ (1,0,0) | 5.806[a] | {4.19 | 5.06} |
| $Y_t, ENG_{2t}, EMP_t$ | 4.359[b] | {3.38 | 4.02} |
| Post-transformation period | | | |
| $Y_t, ENG_{1t}, EMP_t$ (1,0,0) | 4.772[b] | {3.38 | 4.02} |
| $Y_t, ENG_{2t}, EMP_t$ (1,0,0) | 5.094[a] | {4.19 | 5.06} |

*Note*: These tests are conducted under the 1% level of significance.

[a] Refers to the bounds tests for the unrestricted intercept and unrestricted trend.

[b] Refers to the bounds tests for the unrestricted intercept and restricted trend case.

causality, since it only examines whether past changes help to explain current changes. As indicated by Granger and Newbold [27], integrated series have a tendency to “wander” and it is often the case that a regression of one on the other will appear to yield significant results, even if the two series are completely independent. Philips [28] showed that there is an analytic basis for this result as well. As a cure to this problem, Engle and Granger [29] and Granger [30] developed the idea of the Vector Error Correction Model (VECM). The error correction terms which are derived from long-term cointegrating relationships open up an additional channel for Granger causality to emerge that is completely ignored by the standard Granger causality. That is, in addition to the direction of Granger causality among variables, the VECM approach allows for distinguishing between short-term and long-term causality. Even though this was a theoretically useful tool for testing for causality in integrated or cointegrated VAR systems, the complicated pretesting procedure (i.e. estimation of unit roots, analysis of cointegration properties and sensitivity for improper lag establishment) turned out to be a serious difficulty in empirical applications. Fortunately, another solution was proposed by Toda and Yamamoto [31]. Their procedure does not require knowledge of the cointegrating properties of the system and thus avoids the potential bias associated with cointegration tests. In other words, their approach allows application of the asymptotic distribution theory for VAR systems regardless of the order of integration of considered variables or the dimension of cointegration space. This method proved to be particularly advantageous not least because of its flexibility but also its simplicity since in fact, it is only a little modification of the standard Wald test.

Again as was mentioned earlier however, when some standard assumptions do not hold (especially concerning the distribution of error term), the Toda–Yamamoto approach is also likely to fail. Hence, this leads us to consider the bootstrap technique[3] which we describe in the next section.

As shown in the cointegration analysis in Table 3, since the variables in this study exhibit evidence of cointegration, we will include an error correction, and thereby estimate a suitable VEC model. Given the serious drawback associated with the unrestricted VEC model if the appropriate lag length is not selected, we employ amalgam of techniques – the Akaike [32] Information Criterion (AIC), Schwarz [33] Bayesian Criterion (SBC), and the Hannan–Quinn Criterion (HQC).[4] As was mentioned earlier, in addition to indicating the direction of causality amongst variables, the error correction mechanism also enables us to distinguish between the short-run and the long-run Granger causality. The “short-run” causal impact is measured through the *F*-statistics and the significance of the lagged changes in the independent variables, whereas the “long-run” causal impact is measured through the significance of the *t*-test of the lagged error–correction term.

### 3.3. Bootstrap test algorithm

The bootstrap technique, introduced by Efron [14], is based on resampling the data set to estimate the distribution of a test statistic. Using this distribution can decrease bias in inference by providing more precise critical values. Since this technique is based on the empirical distribution of the underlying data set, it is not sensitive to assumption of normality. Another important issue to take into account is the presence of autoregressive conditional heteroscedasticity (ARCH) in our data. In order to guarantee that the presence of ARCH effects

[3] The bootstrap technique has been recently applied by many authors including Ko [9]; Narayan and Prasad [34], Hacker and Hatemi [8], Narayan and Prasad [35], Lach [18], and Gurgul and Lach [36].

[4] In all cases in this paper, AIC, SBC and HQC pointed to an optimal lag length of 2.

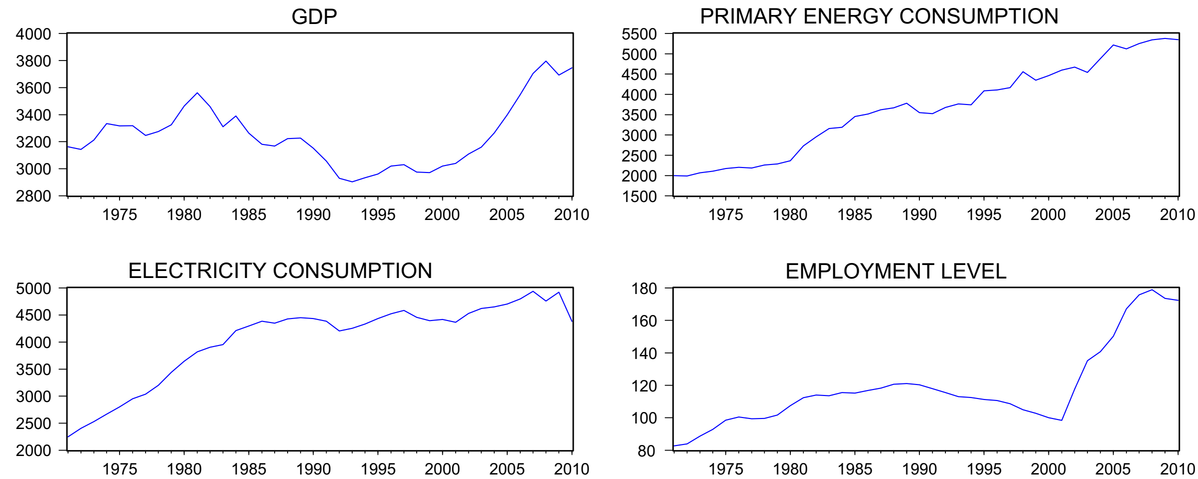


**Fig. 1.** Plots of the data.

does not render bias in estimated results, we use the leveraged bootstrap as suggested by Hacker and Hatemi [8].[5] To minimize experimental randomness and coupled with the fact that recent academic literature concerning the establishment of the number of bootstrap replications has attracted considerable attention, special care is taken in choosing the number of bootstrap samples. Specifically, we employ the method of Andrews and Buchinsky [37] in establishing the number of bootstrap replications. As in Gurgul and Lach [38], our goal in each case was to choose such a value of number of replications which would ensure that the relative error of establishing the critical value would not exceed 5% with a probability equal to 0.95.

It is worth noting that while the bootstrap distribution might seem to perform better than asymptotic theory especially for short time series in many applications, Horowiz [19] as quoted in Gurgul and Lach [36] indicate that the method cannot be treated as a perfect tool for solving all possible model specification problems. Instead, the approach is likely to fail in some specific cases and therefore should not be used without second thought.

## 4. Empirical results

In this section, we present the results of the unit root analysis, cointegration, causality links as well as outcomes of size of the tests. In order to reexamine the nature of the dynamic links between energy consumption and economic growth in South Africa over the sample period, we examined two sets of variables, each of which contained economic growth, employment and one energy-related variable.[6]

### 4.1. Data description

The empirical investigation is based on 40 yearly observations. The chosen dataset includes total primary energy consumption per capita, total electricity consumption per capita, real gross domestic product per capita, and total employment in the non-agricultural sector. The data which are sampled from 1971 to 2010 are obtained from the World Bank (WDI) database. In order to avoid spurious results of further causality analysis, we conducted several transformations of our dataset (see [39–41]).

Fig. 1 presents plots of seasonally adjusted variables. The period under study witnessed a relatively unstable development of the South African economy as GDP exhibited both upward and downward tendencies. As can be observed, high prices for gold and other export commodities in the early 1970s sparked a rise in GDP. By the middle of the year however, economic growth slowed and even began to fall not only because of declining gold revenues, but also because of rising prices for oil imports and increased international competition in other traditional export commodities thus leading to a recession in 1976. Strong export growth base on higher gold prices helped the recovery from this recession, but the country was hit by a series of droughts in the 1980s, which seriously affected agricultural output. Per capita GDP declined by more the 10% during the decade reaching its lowest limit in 1994 perhaps due to the political dispensation. Since the transformation in 1994, GDP has exhibited an upward trend with only slight slowdowns in 1996 and 2008. According to the 2009 economic report on South Africa, the average GDP growth from 1994 to 2007 was 3.4%, more than three times the average growth form 1980 to 1994. It should be noted that since the transformation in 1994, due to oversupply of energy and electricity and long-run low tariff, coupled with sustained economic growth, the energy and electricity demand kept an unexpected high growth with electricity demand showing slight drop at the end of 2007. Given the difference in growth pattern as a result of major economic and noneconomic developments, we divide the full sample into two sub-samples namely: the period before the transformation (1971–1994) and the period after the transformation (1995–2010). Doing this will give us an idea as to the robustness of causality in the face of economic and non-economic developments in South Africa and thus help in the establishment of a more comprehensive causal link between energy consumption and economic growth over the sample period. Notwithstanding, we acknowledge that this method even though somehow useful, might have a serious flaw since the power properties of causality tests strongly depend on sample size. Table 2 contains the results of the stationarity analysis. Stock and Watson [42] argue that Granger causality tests are very sensitive to the stationarity of the series. Given the importance of the order of cointegration of variables in performing causality analysis, we use two different tests for unit roots: first, we conducted an Augmented Dickey–Fuller (ADF) unit root test by first setting up a maximal lag length equal to 6 and then using information criteria (AIC and BIC) to choose an optimal lag length

[5] The bootstrap technique is not described here to save space. Interested readers are referred to Efron [14] for introduction of the technique and Hacker and Hatemi [8] for technical details applied in our paper.

[6] Our study uses two proxies for energy consumption in South Africa namely: primary energy consumption and total electricity consumption. Here primary energy consumption refers to the total use of energy before transformation to other end use fuels.

**Table 4**
Long-run elasticities.

| Full sample | | |
|---|---|---|
| Regressors | Coefficient | |
| | $Y_t, ENG_{1t}, EMP_t$ | $Y_t, ENG_{2t}, EMP_t$ |
| Constant | 1.734*** | 2.728*** |
| $ENG_{it}$ | 0.062 | 0.074*** |
| $EMP_t$ | 0.075*** | 0.138*** |
| $ECM_{t-1}$ | −0.154*** | −0.266*** |
| Pre-transformation period | | |
| Constant | 2.638*** | 3.458*** |
| $ENG_{it}$ | 0.004 | 0.014 |
| $EMP_t$ | 0.037 | 0.110 |
| $ECM_{t-1}$ | −0.276*** | −0.398*** |
| Post-transformation period | | |
| Constant | 10.786*** | 4.730 |
| $ENG_{it}$ | 0.651 | 0.259 |
| $EMP_t$ | 0.491*** | 0.152*** |
| $ECM_{t-1}$ | −0.774*** | −0.317*** |

*Note*: $ECM_{t-1}$ is the error correction term.
*** Indicates significance at the 1% level.

from the set {0, 1,…, 6}. Notwithstanding, the results of an ADF test are relatively sensitive to any incorrect establishment of lag parameter. Among many authors, Agiakoglu and Newbold [43] furthermore indicated that the ADF test tends to under-reject the null hypothesis pointing at nonstationarity too often. Hence, to confirm the results of the ADF test, we also apply the Phillips–Perron (PP) test, which is based on a nonparametric method of controlling for serial correlation when testing for a unit root. As with ADF the null hypothesis refers to nonstationarity. As can be observed from Table 2, the *p*-values from both ADF and PP tests reveal that all the four variables under all sample periods considered are nonstationary but first difference stationary or I(1) thus suggesting the need for a cointegration analysis.

## 4.2. Estimation results

The *F*-statistics for the bounds tests from the ARDL-ECM[7] are reported in Table 3. Relevant critical values (see [22]) were used to ascertain whether the null hypothesis of the absence of cointegration between $Y_t$and $ENG_{it}$ and $EMP_t$ for $i=1$ and 2 could be rejected or not. As can be seen from the table, the *F*-Statistic exceeds the 1% upper critical value in all of the 6 cases considered, thus providing evidence in favor of the existence of a co-integrating level relationship between economic growth and the other two variables (energy consumption and employment). The existence of cointegration implies Granger causality [30]; however, cointegration results do not point out the direction of the causality, which may provide even more useful information to the policy-makers.

The long-run estimates[8] from the ARDL approach are shown in Table 4. It should be said that the lag structure for the short-run dynamics of the ARDL-ECM which we chose based on the AIC and SBC criterions is the same as that used for the bounds test. As can be observed, the coefficients of employment are positive under all samples considered but significant only under the full sample and post-transformation periods. This implies that increase in the level of employment would stimulate growth in real per capita GDP. Turning to the energy consumption variables, we see that while the coefficients of primary energy consumption per capita are insignificant (with positive signs) under all samples, total electrical consumption per capita is statistically significant and positively signed under the full sample, thus suggesting a positive correlation between total electricity consumption and real GDP per capita. The one period lagged error correction term is negatively signed and statistically significant at the 10% level, confirming that a long run relationship exists among the variables. The coefficients on the ECMs represent how fast deviations from the long-term equilibrium are eliminated following changes in each variable. Since all coefficients are different from 0, this means that the variables respond to a deviation from the long-term equilibrium in the previous period. What we have done so far is to look at the correlation between the variables. However, it is now known that correlation does not necessarily imply causation in any meaningful sense of that word since in fact econometric graveyard is full of magnificent correlations, which are simply spurious or meaningless. Since the focus of this study is not to test the role of energy in stimulating economic growth but instead examine the direction of causality between these variables, we therefore look at evidence from bootstrapped causality.

### 4.2.1. Primary energy consumption and economic growth

The bootstrap test results for the analysis of primary energy consumption and economic growth together with the asymptotic variant are presented in Table 5.

*4.2.1.1. Full sample (1971–2010).* As can be observed from the short-run analysis in the upper panels of Table 5, the asymptotic tests show that four out of six null hypothesis of non-Granger causality are rejected at the 10% level of significance under the full sample. The long run analysis correlates well with the short-run analysis by indicating a feedback between energy consumption and economic growth. The long-run feedback is confirmed by the significance of the $ECM_{t-1}$ component in $Y_t$ and $ENG_{1t}$ equations. On the other hand, the results based on the bootstrapping distribution show the rejection of three out of six non-Granger causality null hypothesis. Both the long-run and the short-run analysis indicate a unidirectional Granger causality running from energy consumption to economic growth in South Africa. The evidence of causal links is slightly weaker than what we have seen from the asymptotic tests.

*4.2.1.2. Pre-transformation period (1971–1994).* Under the pre-transformation period, we can notice that the asymptotic test result shows more evidence of Granger causality than the full sample by indicating five out of six rejection of the non-Granger causality null hypothesis. In addition to feedback between energy consumption and economic growth as well as economic growth and employment, there is also evidence that employment Granger causes energy consumption in South Africa in the short-run. Turning to the bootstrap empirical distribution, again the evidence of the Granger causality relationship is weaker in the bootstrap test than in the asymptotic test. In fact at the 10% level of significance, three out of six non-Granger causality null hypothesis are rejected. Nevertheless, the causal links established are similar to those of the full sample and both the long-run and the short-run analysis are well supportive of each other. The unidirectional Granger causality established by the bootstrap tests during this

[7] The TREND variable is included into the testing model since the series showed some form of trending pattern (see Fig. 1).

[8] Even though diagnostics checks on the model failed to suggest evidence of any problem with the model, we point out that these estimates might not be very reliable since other factors influencing energy consumption such as energy prices, capital, industry structure, ect., are not accounted for. This however, shall be the focus of future research.

**Table 5**
Analysis of causal links between $Y_t$, $ENG_{1t}$ and $EMP_t$ (VEC model).

| Short-run | | | | | | |
|---|---|---|---|---|---|---|
| Null hypothesis[a] | p-value | | | | | |
| | Asymptotic test | | | Bootstrap test | | |
| $ENG_{1t} \nrightarrow Y_t$ | **(0.071)** | **[0.099]** | **{0.012}** | **(0.001)** | **[0.082]** | {0.148} |
| $Y_t \nrightarrow ENG_{1t}$ | **(0.018)** | **[0.080]** | {0.129} | (0.201) | [0.866] | **{0.097}** |
| $ENG_{1t} \nrightarrow EMP_t$ | (0.397) | [0.226] | **{0.013}** | (0.130) | [0.110] | {0.206} |
| $EMP_t \nrightarrow ENG_{1t}$ | (0.101) | **[0.072]** | **{0.001}** | (0.200) | [0.301] | {0.992} |
| $Y_t \nrightarrow EMP_t$ | **(0.060)** | **[0.073]** | {0.654} | **(0.000)** | **[0.073]** | **{0.000}** |
| $EMP_t \nrightarrow Y_t$ | **(0.082)** | **[0.064]** | **{0.020}** | **(0.000)** | **[0.000]** | {0.200} |
| **Long-run** | | | | | | |
| Equation | p-value of $ECM_t$ component | | | | | |
| | Asymptotic test | | | Bootstrap test | | |
| $ENG_{1t}$ | **(0.058)** | **[0.014]** | **{0.011}** | (0.211) | [0.121] | {0.180} |
| $Y_t$ | **(0.052)** | **[0.021]** | {0.163} | **(0.012)** | **[0.015]** | **{0.022}** |
| $EMP_t$ | **(0.043)** | [0.221] | **{0.052}** | **(0.044)** | **[0.024]** | {0.120} |

**Note:** [a] The notation "$x \nrightarrow y$" is equivalent to "x" does not Granger cause "y"; (.) indicates full sample period; [.] represents pre-transformation period, {.} indicates post-transformation period. Figures in bold face indicates significance at the 10% level and hence rejection of the null hypothesis that "x" does not Granger cause "y".

period is not surprising since the economy depended primarily on high-scale energy-intensive mining activities with gold being the key focus. A sudden increase in gold price in the 1970s to a peak in 1980 was accompanied by the biggest ever production of gold in South Africa; which skewed the national statistics at the time. In fact, gold contributed more than 27% of GDP during this period [7].

*4.2.1.3. Post-transformation period (1995–2010).* As with the full sample, the asymptotic tests under the short-run analysis show four rejection of the non-Granger causality null hypothesis. The nature of causal links established is somehow different from the full sample and the pre-transformation sample. For the bootstrap tests, only two non-Granger causality null hypothesis are rejected, showing a unidirectional Granger causality running from economic growth to energy consumption.

In summary, it can be observed that results from the asymptotic test are somehow different from results based on the bootstrap empirical distribution. In fact, over all sample periods considered, the evidence of Granger causality is weaker in the bootstrap tests than the asymptotic tests. This is consistent with the findings of Lach [18] that the standard asymptotic approach causes significant over-rejection of the non-Granger causality hypothesis. More besides, it appears that the smaller the sample size is implemented in the test, the weaker the evidence of the Granger causality based on the bootstrap test. It should be mentioned that while the nature of causal links seems to be influenced by the analyzed period, for the most part, the asymptotic tests provide a basis for concluding that there exists bidirectional Granger causality between energy consumption and economic growth in South Africa. However, the bootstrap tests show evidence of a unidirectional Granger causality running from energy consumption to economic growth in both the short and long runs. In addition, there is also evidence of feedback between economic growth and employment in the short-run. Since this study relies on evidence from the bootstrap tests, the unrestricted VEC model provides us a ground for concluding a unidirectional Granger causality running from energy consumption to economic growth (in the long-run and short-run) and a feedback between economic growth and employment in South Africa (in the short-run). The nature of causal links between primary energy consumption and economic growth in South Africa appears to be similar over all samples (only different in the short-run analysis for the post-transformation period) indicating that the transformation in 1994 did not affect the causal relationship much. The unidirectional causality from primary energy consumption to economic growth should not be surprising since we have seen that the South African industry which constitutes a large percentage of GDP is energy intensive (accounts for over 43.4% of total final energy consumption), that is, it uses large amounts of energy for every dollar of added value, compared with industries in the developed world. Coal alone accounts for more than 50% of all industrial energy. Based on our own calculations from South African data, even though there has been some slight reduction in the level of net coal exports recently [net exports/imports (−)], it has still remained very high, maintaining an average of 72,412.7 thousand short tons between 2000 and 2009. We can therefore argue that coal has been a driving force behind South Africa's economy and hence, the causal link between primary energy consumption and economic growth is not surprising. Since this could imply that growth in primary energy consumption in South Africa implies increase in the use of coal, our finding may have some environmental implications.

*4.2.2. Total electricity consumption and economic growth*

Results for the analysis of total electricity consumption and economic growth together with the asymptotic variant are presented in Table 6. Again, it can be observed that the results of the bootstrap tests over the sample periods are greatly different from the results of the asymptotic test. The Granger causality in the bootstrap tests is also weaker, showing evidence of a unidirectional short-run and long-run Granger causality running from electricity consumption to economic growth under all test periods. In general, the causal links established by the bootstrap test in this analysis is some how similar to the previous analysis involving primary energy consumption and economic growth.

**Table 6**
Analysis of causal links between $Y_t$, $ENG_{2t}$ and $EMP_t$ (VEC model).

| Short-run | | | | | | |
|---|---|---|---|---|---|---|
| Null hypothesis[a] | p-value | | | | | |
| | Asymptotic test | | | Bootstrap test | | |
| $ENG_{2t} \nrightarrow Y_t$ | **(0.075)** | **[0.007]** | **{0.016}** | **(0.000)** | **[0.010]** | **{0.016}** |
| $Y_t \nrightarrow ENG_{2t}$ | **(0.082)** | **[0.092]** | {0.202} | (0.260) | [0.551] | {0.486} |
| $ENG_{2t} \nrightarrow EMP_t$ | (0.875) | [0.249] | **{0.065}** | (0.142) | [0.306] | {0.132} |
| $EMP_t \nrightarrow ENG_{2t}$ | **(0.049)** | [0.580] | {0.113} | **(0.000)** | [0.323] | {0.398} |
| $Y_t \nrightarrow EMP_t$ | **(0.022)** | **[0.073]** | **{0.045}** | (0.419) | [0.148] | **{0.000}** |
| $EMP_t \nrightarrow Y_t$ | (0.399) | **[0.064]** | **{0.029}** | **(0.000)** | **[0.009]** | {0.114} |
| Long-run | | | | | | |
| Equation | p-value of $ECM_{t-1}$ component | | | | | |
| | Asymptotic | | | Bootstrap | | |
| $ENG_{2t}$ | **(0.054)** | **[0.023]** | **{0.091}** | (0.201) | [0.151] | {0.213} |
| $Y_t$ | **(0.042)** | **[0.051]** | {0.382} | **(0.004)** | **[0.022]** | **{0.021}** |
| $EMP_t$ | **(0.009)** | [0.198] | **{0.o17}** | **(0.006)** | **[0.012]** | **{0.100}** |

We point out that our finding is different from the finding of Odhiambo [6] on South Africa. The difference in finding could be attributed to two main factors: first, we employed an alternative method which does not follow asymptotic theory and since the estimated distribution depends only on the available dataset, it may be reasonable to expect that the bootstrap approach does not require such strong assumptions as the approach used by Odhiambo [6]. Second, as a proxy for electricity consumption, Odhiambo [6] used the residential electricity consumption/capita. Eventhough residential electricity consumption accounts for 17% of electricity demand, this might not reflect the true welfare or income level for a country like South Africa given that the country has one of the lowest electricity prices in the world. More besides, the free basic electricity Subsidy in South Africa (implemented in 2003) which entitles all households to 50 kWh of electricity every month is likely to influence residential demand and consumption patterns. It would therefore be necessary for the electricity proxy to capture the industrial sector, not least because this is the most important sector of economic activites in South Africa, but also because the sector accounts for over 66% of total electricity consumption. Given the following, we argue that the results in this paper are likely to be more reliable. our finding implies that reducing energy consumption could lead to a fall in income. This result has a lot of significance on the South African economy which implies that the country is highly energy dependent. The lack of feedback from economic growth may mean that as regular growth of energy supply is germane in boosting economic output; however, additional income or economic growth does not translate into adequate demand in the energy sector, and thus does not stimulate additional energy consumption.

### 4.2.3. Size and power properties

We emphasize here that even though several authors have shown that the asymptotic test statistics constructed from the small sample data might suffer from size distortion (e.g., [8,9,17,18,20]), it is not sufficient to draw conclusion that the evidence from the bootstrap test is more convincing and reliable than the asymptotic test in this application. For this purpose, we compare the size and power properties of the two test methods. Given that the underlying distribution of the data in this study shows little evidence of normality, we adopt a student's $t$ distribution for the tests which we believe to be a more appriopriate assumption than than Gaussian normal distribution.[9]

We hasten to emphasize that since this part of the paper is only complementary, detailed explaination and information regarding the DGP process used in Monte Carlo Study is not presented. Nowithstanding, such details would certainly be made available upon request from the authors.

The size of the 10% test is tabulated in Figs. 2–4. The upper panel of the figures summarizes the size of the asymptotic tests while the lower panel summarizes the size of the bootstrap tests. Since the nominal size of the test is 10%, the ideal value of a test should be 0.1. We see that in upper panel of Fig. 2, the size of the asymptotic test is more than mid-way between 10% and 20%. For the pre-transformation period (as the upper panel of Fig. 3 displays), where the sample size became smaller, the size of the asymptotic test increased by a larger percentage. For the post-transformation period (as the upper panel of Fig. 4 displays), where the sample size became even much smaller, the magnitude of the size of the asymptotic test rises up to almost 43%. In contrast, as what can be seen in the lower panels of Figs. 2–4, the size of the bootstrap test does not change much and remains stable around the nominal 10% significance level. More besides, the size of the bootstrap test is lower than that of the asymptotic test in all samples. As in Ko [9], the Monte Carlo study shows that the asymptotic test has larger size distortion than the bootstrap test in this application. This finding implies that the asymptotic Granger causality test suffers size distortion problem for South African data and hence, more evidence on the causal links between energy consumption and economic growth in South Africa is needed. This goes to suggest that the evidence on the nature of causal links established in this study are likely to be more reliable for South Africa.

[9] To test the sensitivity of the choice of distribution, we also applied a variety of distributions of error term in comparism with the the student's t distribution. However, the results obtained were quite similar.

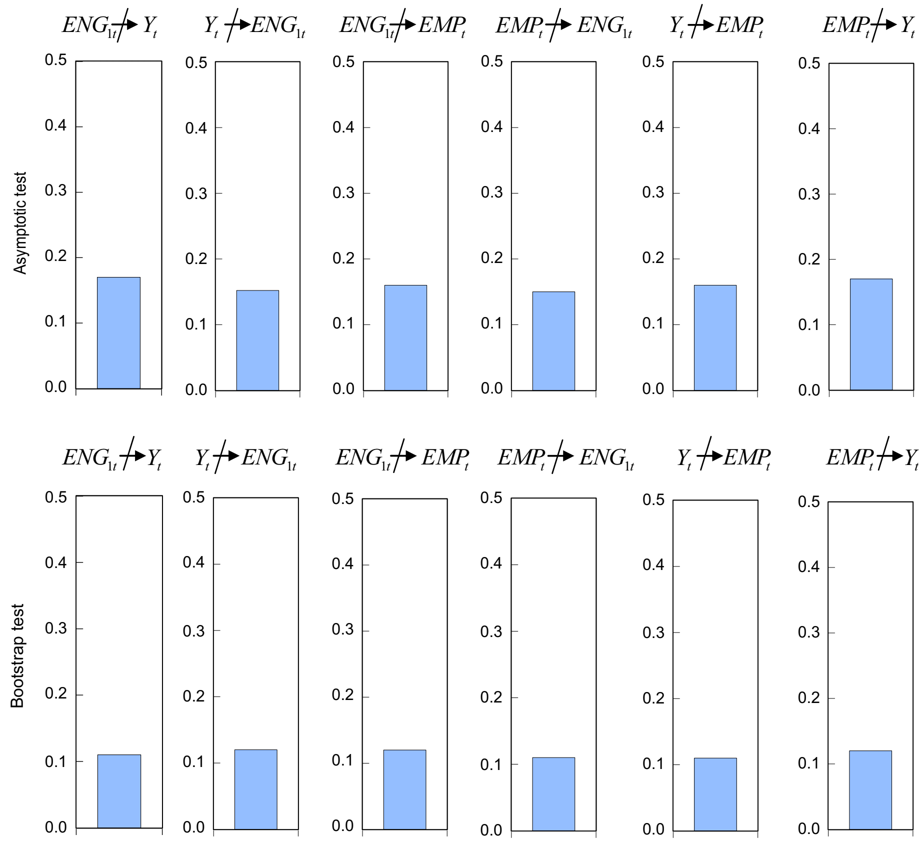


**Fig. 2.** Size of the test: full sample period (1971–2010).

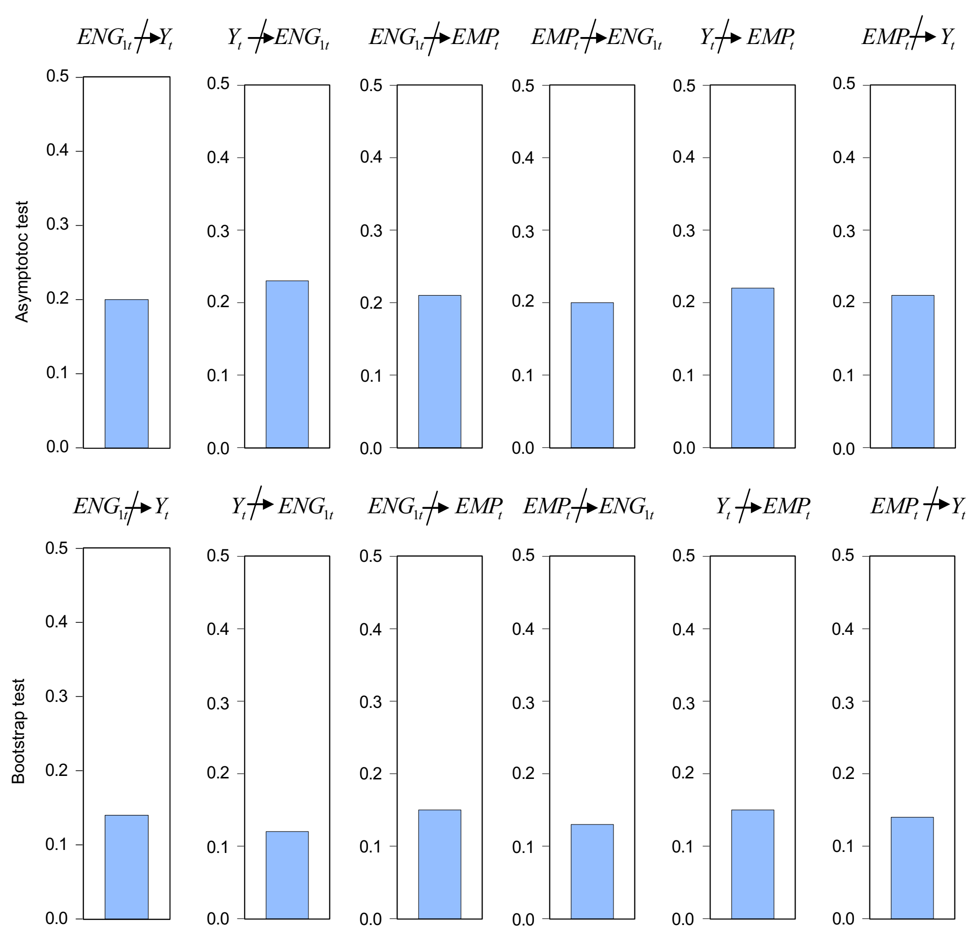


**Fig. 3.** Size of the test: pre-transformation period (1971–1994).

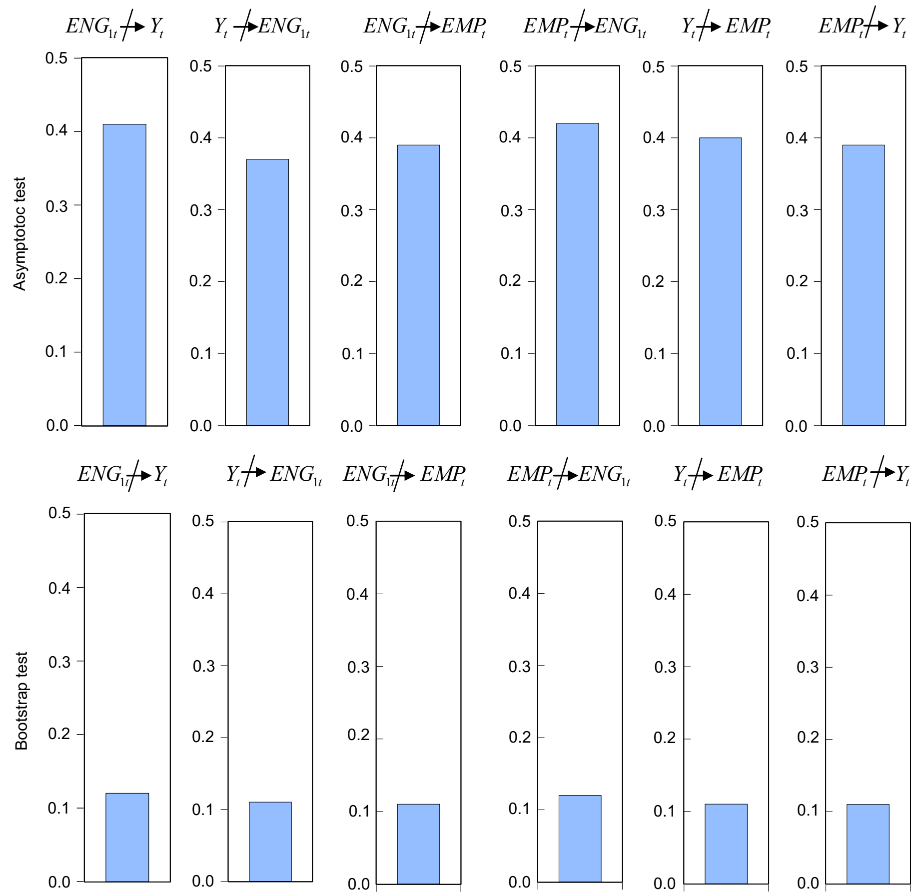


**Fig. 4.** Size of the test: post-transformation period (1995–2010).

## 5. Conclusion and policy implications

The purpose of this paper is to reassess the existing evidence of causal interdependence between energy consumption and economic in South Africa. In so doing, we propose the application of a bootstrap test. Unlike traditional parametric approaches, the method is used for estimating the distribution of a test statistic by resampling the data non-parametrically. Since the estimated distribution depends only on the available dataset, it may be reasonable to expect that the bootstrap approach does not require such strong assumptions as parametric methods. Our research was conducted for primary energy consumption as well as for the total consumption of electricity. In order to reflect the causality between energy consumption and economic growth properly, we performed our investigations in a three-dimensional framework with employment chosen as an additional variable. The empirical applications to reliable South African data (1971–2010) document significant improvement in the size and power of the bootstrap test over the asymptotic test. Due to diverse economic developments over the sample period and to as well check the stability of causal links, the investigations were performed on three samples: a full sample, a pre-transformation sample and a post-transformation sample. The main findings are: first, there is evidence of long-run unidirectional Granger causality running from energy consumption to economic growth and feedback between employment and economic growth in the short-run. Second, the long run estimates reinforce the Granger causality tests by indicating that energy consumption is positively correlated with economic growth in the long-run. Third, evidence from a further Monte Carlo study revealed that the asymptotic Granger causality test suffers size distortion problem for South African data, and hence, suggesting the need for more empirical evidence on South Africa. This in fact suggests the the results presented in this study are likely to be more reliable than the previous evidence on South Africa.

The results have serious significance on the South African economy. First, this may mean that the country is highly energy dependent and that a fall in energy consumption leads to a drop in income. In fact, this assertion should not be surprising since we have noticed that the South African economy is energy intensive with industry which constitutes a large percentage of GDP accounting for over 43.4% of total final energy consumption. Second, the lack of feedback from economic growth may mean that focus of the economy on the energy sector has not been adequate in South Africa. Third, energy conservation policies will negatively impact economic growth in South Africa. Furthermore, South Africa being a highly energy dependent country, will have the performance of its employment formation on the economy partly determined by adequate energy. Finally, our results have serious environmental implications and suggest that energy use in South Africa would have a long run effect of raising the country's $CO_2$ emission levels. Hence, the government might need to develop a more balanced energy structure which will include higher share of renewable energy.

For future research, it would be necessary to follow similar lines as Wesseh et al. [44] and Lin and Wesseh [45]. Indeed, given the serious adverse environmental implication from the consumption of coal in South Africa, it is important to examine the possibilities of energy substitution.

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